ARL-SR-0345 ● Nov 2015

US Army Research Laboratory

Instructional Management for Adaptive Training and Education in Support of the US Army Learning Model–Research Outline

by Benjamin Goldberg, Anne Sinatra, Robert Sottilare, Jason Moss, and Arthur Graesser

NOTICES

Disclaimers

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REPORT DOCUMENTATION PAGE			Form Approved OMB No. 0704-0188

1. REPORT DATE *(DD-MM-YYYY)* November 2015	**2. REPORT TYPE** Special	**3. DATES COVERED (From - To)** 1 October 2014–15 July 2015
4. TITLE AND SUBTITLE Instructional Management for Adaptive Training and Education in Support of the US Army Learning Model–Research Outline		**5a. CONTRACT NUMBER** **5b. GRANT NUMBER** **5c. PROGRAM ELEMENT NUMBER**
6. AUTHOR(S) Benjamin Goldberg, Anne Sinatra, Robert Sottilare, Jason Moss, and Arthur Graesser		**5d. PROJECT NUMBER** **5e. TASK NUMBER** **5f. WORK UNIT NUMBER**
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) US Army Research Laboratory ATTN: RDRL-HRT-T Aberdeen Proving Ground, MD 21005-5425		**8. PERFORMING ORGANIZATION REPORT NUMBER** ARL-SR-0345
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)		**10. SPONSOR/MONITOR'S ACRONYM(S)** **11. SPONSOR/MONITOR'S REPORT NUMBER(S)**

12. DISTRIBUTION/AVAILABILITY STATEMENT

Approved for public release; distribution is unlimited.

13. SUPPLEMENTARY NOTES

14. ABSTRACT

While human tutoring and mentoring are common teaching tools, current US Army standards for training and education are group instruction and classroom training, also known as one-to-many instruction. Recently, the US Army has placed significant emphasis on self-regulated learning (SRL) methods to augment institutional training where Soldiers will be largely responsible for managing their own learning. In support of the US Army Learning Model and to provide affordable, tailored SRL training and educational capabilities for the US Army, the US Army Research Laboratory is investigating and developing adaptive tools and methods to largely automate the authoring (creation), delivery of instruction, and evaluation of computer-regulated training and education capabilities. A major goal within this research program is to reduce the time and skill required to author, deliver, and evaluate adaptive technologies to make them usable by a larger segment of the training and educational community. This research includes 6 interdependent research vectors: individual learner and unit modeling, instructional management principles, domain modeling, authoring tools and methods, evaluation tools and methods, and architectural and ontological support. This report (1 of 6 interdependent research outlines) focuses on instructional management research for adaptive training and education with the goal of guiding learning in militarily relevant training domains.

15. SUBJECT TERMS

GIFT, design, adaptive training, domain modeling, SRL

16. SECURITY CLASSIFICATION OF:			**17. LIMITATION OF ABSTRACT**	**18. NUMBER OF PAGES**	**19a. NAME OF RESPONSIBLE PERSON** Robert Sottilare
a. REPORT	**b. ABSTRACT**	**c. THIS PAGE**			**19b. TELEPHONE NUMBER (Include area code)**
Unclassified	Unclassified	Unclassified	UU	58	407-208-3007

Standard Form 298 (Rev. 8/98)
Prescribed by ANSI Std. Z39.18

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Preface

This report is 1 of 6 interdependent research outlines in the Adaptive Training research program. Portions of this text, which originated in ARL-SR-0325,[1] appear in all 6 reports to ensure that readers get the same cross-cutting information.

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[1] Sottilare R, Sinatra A, Boyce M, Graesser A. Domain modeling for adaptive training and education in support of the US army learning model–research outline. Aberdeen Proving Ground (MD): Army Research Laboratory (US); June 2015. Report No.: ARL-SR-0325.

1. Introduction

Training and education tools and methods must be of sufficient intelligence to understand the needs of individual learners and units of learners to mitigate negative learner states and to guide and tailor instruction in real time to optimize learning. These tools and methods must also be affordable, effective, and easy to access and use. These requirements are enablers of the US Army Learning Model (ALM), which includes an emphasis on self-regulated learning (SRL), where Soldiers are expected to manage their own learning and career development through the growth of metacognitive (e.g., reflection), self-assessment, and motivational skills (Butler and Winne 1995). While SRL skills are difficult to train and develop, support may be provided to the learner through "adaptive training technologies" (tools and methods) that may be focused to guide learning and reinforce SRL principles.

To support ALM, the US Army Research Laboratory (ARL) has developed a program of research called "adaptive training" that includes 6 interdependent research areas or vectors: individual learner and unit modeling, instructional management principles, domain modeling, authoring tools and methods, evaluation tools and methods, and architectural and ontological support for adaptive training. The reports documenting these vectors expand the scope of the adaptive tutoring research described in ARL-SR-0284 (Sottilare 2013) to support ALM requirements in the mid- and long-term evolution of training and educational technology: the Synthetic Training Environment and the Future Holistic Training Environment for Live and Synthetic.

This report (1 of 6 interdependent research outlines) focuses on instructional management research for adaptive training and education. An overarching goal of instructional management is to leverage prior research in the learning sciences and artificial intelligence (AI) communities (both theoretical and empirical) to establish a set of best practices on how to author and execute techniques, strategies, and tactics across any domain of instruction. This is a very large research space (Wang-Costello et al. 2013), so it is important to identify the primary themes for applied instructional management practices.

Today the majority of intelligent tutoring systems (ITSs), a form of adaptive training tool to support one-to-one computer-based instruction, supports well-defined domains in mathematics, physics, and software programming. Since Soldiers operate in more-complex, more-dynamic, and more-ill-defined domains, it is necessary to expand the scope of adaptive training tools and methods to support training and education in these militarily relevant task environments. Instructional

management in adaptive training environments represents pedagogical logic and policies that dictate what is experienced and what assistance is provided. The goal is to align instructional management techniques with empirical research that informs what strategies have the greatest influence on performance, retention, and transfer. Effective instructional management research will dictate how best to instruct a particular task or set of concepts for a given type of learner that promotes the development of knowledge and skill across any domain of instruction.

2. Research Goals and Objectives

The goal of the research described in this report is to model militarily relevant training domains to support individually tailored and intelligently guided training experiences as prescribed by the ALM (US Army Training and Doctrine Command 2011). The research provides guidelines, best practices, tools, models, and methods in support of this research goal. More specifically, we intend to accomplish the following:

- Discover and deliver personalized and adaptive training experiences that are informed by experimentation or prior research on tutoring methods and techniques that are moderated by individual differences of a learner, or team of learners, to promote efficient knowledge and skill acquisition across technology-driven training applications.
- Research, design, and develop prototype authoring tools grounded in learning and instructional theory and informed by empirical research to assist training managers, developers, and subject matter experts (SMEs) in building pedagogically sound training experiences without the requirement of programming.
- Discover and develop modeling functions that account for uncertainty across policies informing pedagogical decisions (e.g., content delivery, course navigation, and guidance) with an ability for these functions to refine and optimize themselves through reinforcement learning mechanisms over time as new interaction and performance data becomes available (e.g., Markov Decision Processes).

In this research outline, we present the goals associated with the instructional management research vector and review specific subvectors across the program that influence the approach and direction of our dedicated efforts. This outline emphasizes desired functions and capabilities for ARL's Generalized Intelligent Framework for Tutoring (GIFT), an open-source architecture intended to support adaptive instruction.

3. Background

While human tutoring and mentoring are common teaching tools, current US Army standards for training and education are group instruction and classroom training, also known as one-to-many instruction. Group instruction and classroom training have been generally focused on acquiring and applying knowledge in proxies for live training environments (e.g., desktop simulations, virtual simulations, constructive simulations, and serious games).

Classroom training, especially for complex topics, is often taught as a series of lists that the instructor goes through in a linear fashion (Schneider et al. 2013). This approach puts a heavy burden on the learner to build mental models and make conceptual connections. Using this instructional methodology may lead to varying degrees of success due to individual differences in skills, traits, and/or preferences. In this fashion, lower-performing students who struggle are provided more hands-on guidance while higher-performing students who are under-challenged (e.g., bored) are allowed to progress through a course at an accelerated rate.

Small group instruction in live environments has also been used to assess application of knowledge and the development of skills. A standard feedback mechanism for US Army training is the after-action review (AAR), where significant decision points and actions are captured for small group discussions conducted after the completion of a training event to help capture teachable moments and to aid Soldiers in reflecting on their recent training experiences.

Both classroom training and small group instruction are manpower-intensive, requiring teachers, mentors, and support staff to guide the Soldier's experience. Today ITSs guide learner training and education primarily in physically static (e.g., desktop simulations), well-defined domains. Research is needed to expand ITS instructional management practices to support militarily relevant domains that train across knowledge, skills, and abilities required to be successful Soldiers. The focus of this research is to identify pedagogical principles that can be applied to manage knowledge and skill acquisition by addressing individual differences, managing affective states experienced during learning, supporting metacognitive development, enforcing reflection through personalized AARs, and promoting retention and transfer to operational environments.

3.1 Self-Regulated Learning and the US Army Learning Model

In 2011 the US Army placed significant emphasis on the development of SRL skills with the expectation that new methods of instruction (e.g., ITSs) would augment institutional training (i.e., classroom and small group instruction).

One-to-one human tutoring has been shown to be significantly more effective than one-to-many instructional methods (e.g., traditional classroom instruction) (Bloom 1984; VanLehn 2011). However, it is neither practical nor affordable to have one expert human tutor to mentor each Soldier in the US Army for every required operational task. This alone signals the need for capabilities to support one-to-one, tailored training and educational experiences.

Additionally, under the ALM, Soldiers are largely responsible for managing their own learning, but SRL skills are difficult to train and develop (Azevedo et al. 2009; Butler and Winne 1995; Graesser and McNamara 2010). We anticipate adaptive training tools and methods will fill this gap and provide personalized guidance to acquire, apply, retain, and transfer knowledge and skills to the operational environment. This signals the need for a computer-regulated learning strategy to augment missing SRL skills; however, adaptive training technologies must first become affordable, sufficiently adaptive, and easy to use for this strategy to be realized.

3.2 Motivation for Research

A promising alternative to one-to-one human tutoring is one-to-one adaptive training tools that include ITSs. Meta-analyses and reviews support the claim that ITS technologies routinely improve learning over classroom teaching, reading texts, and/or other traditional learning methods. These meta-analyses normally report effect sizes (sigma [σ]), which refer to the difference between the ITS condition and a control condition in standard deviation units. The reported meta-analyses show positive effect sizes that vary from $\sigma = 0.05$ (Dynarsky et al. 2007) to $\sigma = 1.08$ (Dodds and Fletcher 2004) but most hover between $\sigma = 0.40$ and $\sigma = 0.80$ (Fletcher 2003; Graesser et al. 2012; Ma et al. in press; Steenbergen-Hu and Cooper 2013, 2014; VanLehn 2011). Our current best meta-meta estimate from all of these meta-analyses is $\sigma = 0.60$. This performance is comparable to human tutoring, which varies from between $\sigma = 0.20$ and $\sigma = 1.00$ (Cohen et al. 1982; Graesser et al. 2011) depending on the expertise of the tutor. Human tutors have not varied greatly from ITSs in direct comparisons between ITS and trained human tutors (Olney et al. 2012; VanLehn 2011; VanLehn et al. 2007).

Graesser et al. (2015 in press) are convinced that some subject matters will show higher effect sizes than others when comparing any intervention (e.g., computer trainers, human tutors, group learning) with a control. It is difficult to obtain high effect sizes for literacy and numeracy because these skills are ubiquitous in everyday life and habits are automatized. For example, Ritter et al. (2007) reported that Cognitive Tutor software for mathematics has shown an effect size of $\sigma = 0.30$

to 0.40 in environments with minimal control over instructors. Human interventions to improve basic reading skills typically report an effect size of $\sigma = 0.20$. In contrast, when the student starts essentially from ground zero, such as many subject matters in science and technology, effect sizes are expected to be more robust. ITSs show effect sizes of $\sigma = 0.60$ to 2.00 in the subject matters of physics (VanLehn 2011; VanLehn et al. 2005), computer literacy (Graesser et al. 2012; Graesser et al. 2004), biology (Olney et al. 2012), and scientific reasoning (Halpern et al. 2012; Millis et al. 2011). As a notable example, Digital Tutor software (Fletcher and Morrison 2012) improves information technology by an effect size as high as $\sigma = 3.70$ for knowledge and $\sigma = 1.10$ for skills. The effect sizes attributed to improved instruction and improved domain knowledge have not been separated in this analysis. Such large effect sizes would never be expected in basic literacy and numeracy.

Overall, these are promising results and equate to an increase of about a letter grade improvement over traditional classroom instruction. While ITSs are a promising technology to support adaptive training for individuals in well-defined domains like mathematics, physics, and computer programming, the US Army requires the ability to develop and exercise Soldier skills in more ill-defined domains (e.g., leadership) and at the unit level (e.g., collaborative learning and team training). Developing and maintaining the ability to make effective decisions under stress and in complex environments is also desirable.

Adaptive systems by their nature require additional content and complexity to support tailored learning for each user and as a consequence have a very high development cost, a major barrier to adoption by the US Army. Adaptive systems are also insufficiently adaptive to support tailored, self-regulated training and educational experiences across a broad spectrum of military tasks as required by the ALM. Today, few ITS authoring tools are generalized across all of the domains requiring training, and no evaluation criteria or standards have been developed to promote reuse and interoperability among ITSs (Sottilare et al. 2012b). In other words, current adaptive systems are not yet intelligent enough to support the tailored instruction required by the US Army in the breadth of domains being trained, but there is a stable foundation of 50 years of science on which to grow an adaptive training and education capability for the US Army.

3.3 Adaptive Training and Education Definitions

In support of the ALM and affordable adaptive training and educational capabilities for the US Army, ARL is investigating and developing adaptive tools and methods. A desired end-state is the automation of authoring (creation) processes, instruction,

and evaluation of computer-regulated training and education capabilities to help build SRL skills and support mixed-initiative interaction. A major goal within this research program is to reduce the time/cost and knowledge/skill required to author, deliver, and evaluate adaptive technologies to make them usable by a larger segment of the Army training and educational community.

Adaptive training and education research includes elements of adaptive tutoring, distributed learning, virtual humans, and training effectiveness evaluation. For additional detail on research specific to ITSs, refer to ARL-SR-0284 (Sottilare 2013). The following definitions are provided for this section to distinguish between adaptive training and education elements and also to highlight their relationships:

Adaptive Tutoring: Also known as intelligent tutoring, these tailored instructional methods provide one-to-one and one-to-many computer-guided experiences focused on optimizing learning, comprehension, performance, retention, reasoning, and transfer of knowledge and acquired skills to the operational environment.

Adaptive Tutoring Systems: Also known as ITSs, these mechanisms or technologies (tools and methods) provide tailored training and educational experiences. Adaptive tutoring systems respond to changing states in the learner and changing conditions in the training environment to optimize learning and anticipate and recognize teachable moments.

Virtual Humans: Artificially intelligent visual representations of people that simulate or emulate cognitive, affective, physical, and social processes.

Distributed Learning: Concurrent distribution of training and educational content to multiple users at the point of need in which content is intelligently selected to support learning, increased performance, and long-term competency in selected domains.

Training/Learning Effectiveness: Evaluation of the impact of training and educational tools and methods on usability, learning, comprehension, performance, retention, reasoning, and transfer of knowledge and acquired skills to the operational environment.

Adaptive Training and Education Systems: A convergence of ITSs and external training and education capabilities (e.g., serious games, virtual humans, and simulations) to support engaging experiences with reduced need for authoring (Sottilare 2015).

Generalized Intelligent Framework for Tutoring (GIFT) (Sottilare et al. 2012a; Sottilare et al. 2013a): An open-source, modular architecture whose goals are to

reduce the cost and skill required for authoring adaptive training and educational systems, automate instructional delivery and management, and develop and standardize tools for the evaluation of adaptive training and educational technologies.

Adaptive training and education research at ARL are being conducted across 6 interdependent research vectors: individual learner and unit modeling, instructional management principles, domain modeling, authoring tools and methods, evaluation tools and methods, and architectural and ontological support. This report (1 of 6 interdependent research outlines) focuses on domain modeling research for adaptive training systems with the goal of guiding learning in militarily relevant training and educational domains.

Soldiers operate in a variety of complex, dynamic, ill-defined domains where their ability to persevere in the face of adversity, adapt to their situation, collaborate, and think critically are key to the successful completion of their assigned missions. To develop and exercise these skills, it is paramount for Soldiers to train in challenging environments. Currently these few challenging training environments have been largely provided through manpower-intensive methods or systems with little ability to adapt instruction to support their learning needs. To illustrate this point, Franke (2011) asserts that through the use of case study examples, instruction can provide the pedagogical foundation for decision making under uncertainty. However, this approach is limited in implementation by the expanse of potential cases that would need to be consistently updated and maintained to support large populations like the US Army.

As noted previously, adaptive systems like ITSs have been shown to be effective in promoting learning in primarily static (e.g., learners seated at desktop computers) instructional settings within relatively simple, well-defined domains (e.g., mathematics and physics) for individual learners. For our purposes, static instruction includes cognitive, affective, or social training tasks where a desktop computer delivers instruction and where the physical movement of the learner is limited to activities that can be conducted while seated. For example, static instruction can effectively support cognitive tasks involving decision making and problem solving but are less effective for training tasks involving motion and perception (e.g., land navigation and marksmanship). Ideally, we desire portable adaptive instructional capabilities to go with Soldiers to support training and education at their point of need across a wide spectrum of Army operational tasks. Research is needed to develop tools and methods to support broader domain modeling that is representative of the full spectrum of Army operational tasks. Standards, interoperability, and automation (e.g., automated scenario generation) (Zook et al. 2012) will likely play a significant role in making adaptive training

practical. In this way, adaptive training technologies will have the greatest impact on organizational learning in the Army.

4. US Army Requirements for Adaptive Training Systems and Instructional Management Research

The Army science and technology community uses Warfighter Outcomes (WFOs) as the authoritative source for identifying Warfighter needs. WFOs are used to share research and future technology solutions. In the training and education (TandE) domain, the adaptive TandE research program is targeting 4 specific requirements to support the evolution of US Army training: adaptive training and education systems, big data, training at the point of need, and AI.

4.1 Adaptive Training and Education Systems and Instructional Management

The primary gap to be addressed under this Army requirement is the lack of adaptive systems (e.g., intelligent tutors) to support individual and collective (team or unit) training. The Army needs an adaptive training and education capability that is persistent and easy to use/access with minimal start-up time. There are also requirements to automate an informal AAR (also known as postexercise critique) to reduce the time and skills needed to produce the AAR and improve its focus and quality. Another line of thought also notes that the AI in ITSs could be used to facilitate rapid mission planning and course-of-action analyses as a job aid in operational contexts.

An effective adaptive training capability depends on sound instructional management practices. Instructional management practices consist of techniques, strategies, and tactics applied to a domain of instruction to optimize performance outcomes (Sottilare et al. 2014). With respect to GIFT, this vector of research is concerned with identifying instructional best practices that associate with all facets of learning as well as establishing authoring workflows that instantiate those practices across multiple environments of instruction. The goal is to provide adaptive training solutions that are sufficiently tailored for each individual Soldier and for teams of Soldiers.

4.2 Big Data and Instructional Management

The primary gap to be addressed under this Army requirement is that there is a lack of capability to handle and process large amounts of structured and unstructured data (also referred to as big data). One capability needed is a structured data analytics program linking individual data (e.g., achievements) to required long-term competencies in military occupational specialties (MOSs). This would allow Soldiers to understand where they rank in terms of experiences and achievements among other Soldiers in their MOS. It would also allow the Army to identify specific experiences among successful Soldiers in that MOS and provide a model for other Soldiers in that MOS to follow. This data could also be used by course managers and instructors to continuously improve instruction and the mental models of both human and computer-based instructors. Finally, data collected on trainee learning and performance during adaptive training experiences could be used to facilitate unit training management where unit commanders would have access to empirical data to support unit training decisions.

A goal of instructional management in GIFT is to optimize performance and competency outcomes through personalized training experiences that adapt to an individual's knowledge, skills, and abilities (KSAs). A connection between big data and instructional management is applying large datasets from prior course interactions to update and improve technique and strategy implementations across all available courses. A challenge in defining instructional management logic in a domain-independent context is that it requires generalizability across applications. An issue with instructional strategy-based research is that an approach taken in one domain is hard to translate to a different without performing extensive research to validate its application. In addition, it is difficult to define definitive instructional management logic based on these uncertainties. As such, big data can be used to account for this uncertainty by applying machine learning and data mining techniques to assess specific causal relationships between instructional practices and outcomes on performance, retention, and transfer. This application of big data is used to reinforce instructional management models by optimizing itself over time as more and more data is made available.

4.3 Training at the Point of Need and Instructional Management

The primary gap to be addressed under this Army requirement is the lack of an easily accessible, persistent, cost-effective, and low-overhead training environment. A capability is needed to bring training to Soldiers instead of Soldiers going to fixed training locations. This point-of-need training capability would be

easily distributed, web-based, and built upon open-enterprise architecture in the cloud. Army training and educational opportunities would be available on demand anywhere and anytime. However, the delivery mechanism (e.g., laptop computer, mobile device, and smart glasses) for adaptive training is critical in determining the limitations of the domain model scope and complexity. For example, it may be extremely difficult to train all the complexities of a psychomotor task in a desktop computer setting.

A goal of instructional management in GIFT is to support a model of training by convenience and to have mechanisms to support this form of education in the absence of live instruction. Effective training applications administered in a point-of-need capacity requires 4 primary components to deliver sound instruction: 1) the ability to monitor trainee interaction and behavior to accurately assess performance against a granular concept by concept model, 2) the ability to communicate guidance and feedback messages that correspond with individual performance, 3) the ability to adapt scenario/problem elements to maintain appropriate challenge levels for promoting flow, and 4) the ability to manage an automated AAR to review scenario performance and promote reflection on the linkage between outcomes and overall learning objectives. Each of these components depend on each other for the purpose of delivering personalized training experiences through an easily distributed, web-based, open-enterprise architecture. In addition, an optimal adaptive training capability will leverage existing course materials to better serve the development of a competency through point-of-need functions. An example is providing a remedial training activity on an identified weakness between training events to better prepare that individual for the next period of instruction (e.g., recognizing trigger squeeze problems in the Engagement Skills Trainer and providing a remedial multimedia training event prior to the next round of marksmanship instruction on the live range).

4.4 Artificial Intelligence Capabilities and Instructional Management

The primary gap to be addressed under this Army requirement is that the Army lacks an automated capability to replicate the complexity and uncertainty of the operational environment. This gap specifically points to the lack of adaptiveness in virtual humans, intelligent tutoring systems, and other training capabilities. This gap leads to Soldiers developing training response strategies that result in less-challenging training over time along with lower engagement and lower levels of learning and transfer of skills to more challenging operational environments.

A goal of instructional management in GIFT is to facilitate robust AI capabilities that enhance the realism and playability of simulation-based training exercises, specifically those that utilize virtual humans and semi-automated forces. These elements must be embedded with AI capabilities that provide an automated reactive capacity to trainee inputs and actions that adhere to the complexity and uncertainty of an operational environment. In terms of virtual humans, these entities must have logic that supports realistic movements and communication exchanges that reflect back to a culture or operational environment. This requires AI embedded within virtual humans that accounts for cultural norms and customs, along with the ability for the entity to adapt its behavior based on cues and actions perceived from the trainee (rolling of the eyes, change in vocal intonation, failing to account for appropriate cultural greeting, etc.). AI also needs to be embedded in virtual humans that enables their use as virtual teammates in a collaborative training scenario.

This will allow for effective training of team-oriented missions without the requirement of using an all-human team. In terms of semi-automated forces, which are commonly used in tactical training events within environments such as Virtual Battlespace 3 (VBS3), AI techniques must be established that allow a group of forces to adapt their movements over time, as it can autonomously learn from actions and tactics executed by a trainee or team of trainees. This will allow a set of enemy forces to better adapt itself, much like in the real world, for the purpose of creating richer training experiences that increase complexity. In addition, AI techniques must be investigated to ease the development of training scenarios to avoid issues of "replay-ability". A system such as VBS3 would benefit from technologies that enable the generation of multiple scenarios for training purposes based solely around a defined set of tasks, conditions, and standards. This promotes better training because a trainee needs to adapt his/her application of knowledge and skills to an unknown event rather than gaming a scenario by learning the various cues and scripts executed by an enemy entity (i.e., knowing an insurgent is hiding behind a specific door in a specific hallway).

5. Understanding the Dimensions of Instructional Management

There are 4 typical elements that comprise ITSs, a prime example of an adaptive training and education system: a learner or trainee model, an instructional or pedagogical model, a domain model, and some type of user interface. The domain model typically includes an expert or ideal student model by which the adaptive system measures/compares/contrasts the progress of the learner toward learning objectives. The domain model also includes the training environment, the training task, and all of the associated instructional actions (e.g., feedback, questions, hints,

pumps, and prompts) that could possibly be delivered by the adaptive system for that particular training domain. Typical interaction between the learner, the training environment, and the adaptive system (tutoring agents) is shown in Fig. 1.

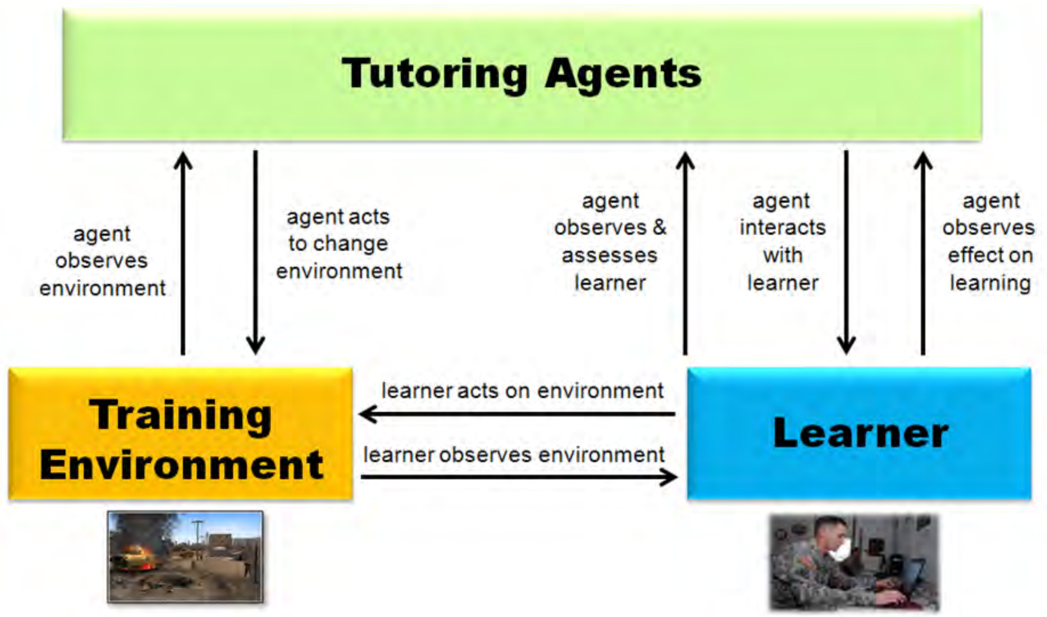

Fig. 1 Adaptive training interaction

Typical training systems examine the interaction between the learner and the training environment to measure progress toward learning objectives. The learner acts on the environment (e.g., opens a door or makes a choice to move into the room or stay outside) and then observes any changes or reactions within the environment. Adaptive systems add a layer of software-based tutoring agents that are designed to guide the learner in much the same way as a human tutor interacts with a learner. The tutoring agents observe the behaviors of the learner to assess their states (e.g., performance and attitudes) and interact with the learner to provide support, direction, and instruction. In addition, they track the effect of interactions on learning. Tutoring agents also interact with the training environment and may manipulate the environment to present more- or less-challenging scenarios in response to the assessed state of the learner.

5.1 Theoretical Foundations of Instructional Management

Instructional strategies have been advocated by researchers and practitioners in many different fields, including education, educational psychology, cognitive and learning sciences, military training, computer-based training, AI in education, computer-supported collaborative learning, educational data mining, etc. (Sottilare et. al. 2014). While these fields often vary across intent and scope of research,

common themes have been recognized across multiple reports involving interdisciplinary research groups organized by the government and research organizations. Examples include (as highlighted in Sottilare et. al. 2014) the following:

- *A Roadmap to Educational Technology*. National Science Foundation, Arlington, VA; 2010. http://www.cra.org/ccc/docs/groe/GROE Roadmap for Education Technology Final Report.pdf.
- *The Army Learning Concept for 2015.* US Army, Washington, DC; 2011. http://www-tradoc.army.mil/tpubs/pams/tp525-8-2.pdf.
- *Committee on Science Learning: Computer Games, Simulations, and Education.* National Academy of Sciences, Washington, DC; 2011. http://www.nap.edu/catalog.php?record_id=13078.
- *Assessing 21st Century Skills.* National Academy of Sciences, Washington, DC; 2011. http://www.nap.edu/catalog.php?record_id=13215#toc.
- *Improving Adult Literacy Instruction*. National Academy of Sciences, Washington, DC; 2012. http://www.nap.edu/catalog.php?record_id=1342.
- *Organizing Instruction and Study to Improve Student Learning*. Institute of Education Sciences of the United States Department of Education, Washington, DC; 2007. http://ies.ed.gov/ncee/wwc/pdf/practice_guides /20072004.pdf.
- *Lifelong Learning at Work and at Home*. American Psychological Association and Association for Psychological Sciences, Washington, DC; 2007. See Graesser AC. Inaugural editorial for *Journal of Educational Psychology*. 2009;101(2):259–261.

These reports emphasize instructional strategies that are supported by empirical tests with scientific methodologies; therefore, the strategies are grounded in science and are evidence-based. It is important that many of the strategies recommended from these groups are geared toward live instruction.

In terms of implementation, instructional management involves both an adaptive outer loop (i.e., adjusting problem selection based on performance outcomes) and an adaptive inner loop (i.e., providing real-time error-sensitive feedback or manipulating the scenario directly) function that accounts for individual differences across KSAs within a given domain. An adaptive, intelligent learning environment needs to launch the right instructional strategies at the right time in a mechanism that attempts to be sensitive to the learner model, maximize learning and motivation, and minimize training time and costs.

5.2 Instructional Management in GIFT

Before we examine specific goals and research interests associated with instructional management in GIFT, it is important to review some high-level components of the architecture. This involves an understanding of how information and data is represented and how these representations ultimately inform the updated Learning Effect Model (LEM) (Sottilare 2015 in press; Sottilare et al. 2015, Fig. 2). The important takeaway of the LEM is the flow of data with respect to the selection of an instructional practice. The effect chain is influenced by both historical data (e.g., prior experience, prior knowledge, and learner traits) maintained over time and real-time data captured during a specific interaction. This data is used to adapt instruction on 2 facets: 1) an inner-loop capacity using data to influence interaction within a single problem or scenario by providing guidance or adjusting difficulty levels similarly to Vygotsky's (1978) zone of proximal development (ZPD) and 2) an outer-loop capacity that configures the next event experienced by a learner based on assessments from a prior event or through predictions based on historical representations and learner traits (VanLehn 2006). This might involve selecting a new problem/scenario, managing a remediation event, moving on to a new section of the course, administering an AAR, or ending the course.

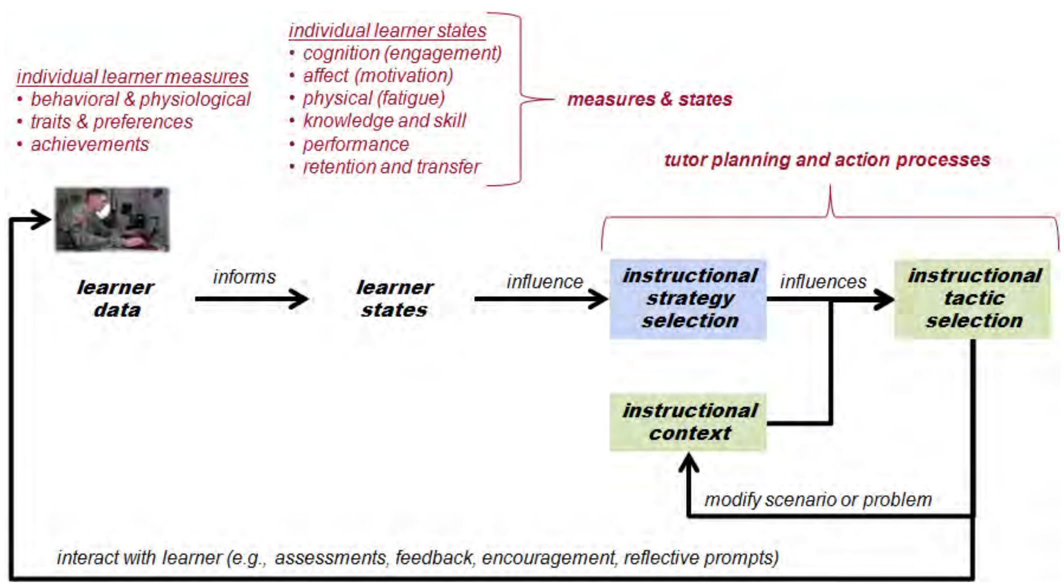

Fig. 2 Updated individual learning effect model (Sottilare 2015 in press; Sottilare et al. 2015)

In terms of the inner-loop adaptive function, Assistive Technology Learning through a Unified Curriculum (ATLEC) primarily interacts on learner assessments occurring in real time for both performance and affective related states. Ultimately,

raw interaction data are used to infer a learner state. This involves robust assessment techniques that can accurately gauge an individual learner's performance for a given task, the affective responses they are having within that task, and their estimated competency for the domain that task is designed to train. This inferred learner state is used to inform the selection of an instructional strategy to mediate the learning experience. In the current baseline of GIFT (GIFT 2015), the instructional strategies supported for the inner loop consists of "provide guidance", "adapt scenario", "administer assessment", and "do nothing". These strategies are represented as high-level domain-independent descriptors of an action the system can take within a given learner event. These high-level actions must then be translated into a specific tactic of execution (see Sottilare et. al. 2014 for a comprehensive breakdown of strategies versus tactics).

For outer-loop adaptive functions, components of the ATLEC are administered up front to configure a lesson's sequence of interaction. Learner data inform strategy selections that associate with Merrill's (1994) Component Display Theory. This interaction is currently encapsulated in a tool used by GIFT called the Engine for Management of Adaptive Pedagogy (EMAP) (see Fig. 3). In the latest GIFT baseline, the EMAP is used to guide a learner through a set of interactions that focuses on 1) presentation of rules for a domain or task, 2) presentation of examples where those rules are being applied, 3) administering of a knowledge assessment that gauges a learner's ability to recall facts, and 4) administering of a practice assessment that gauges a learner's skill for performing tasks associated with the domain of instruction (Goldberg et al. 2012; Wang-Costello et. al. 2013).

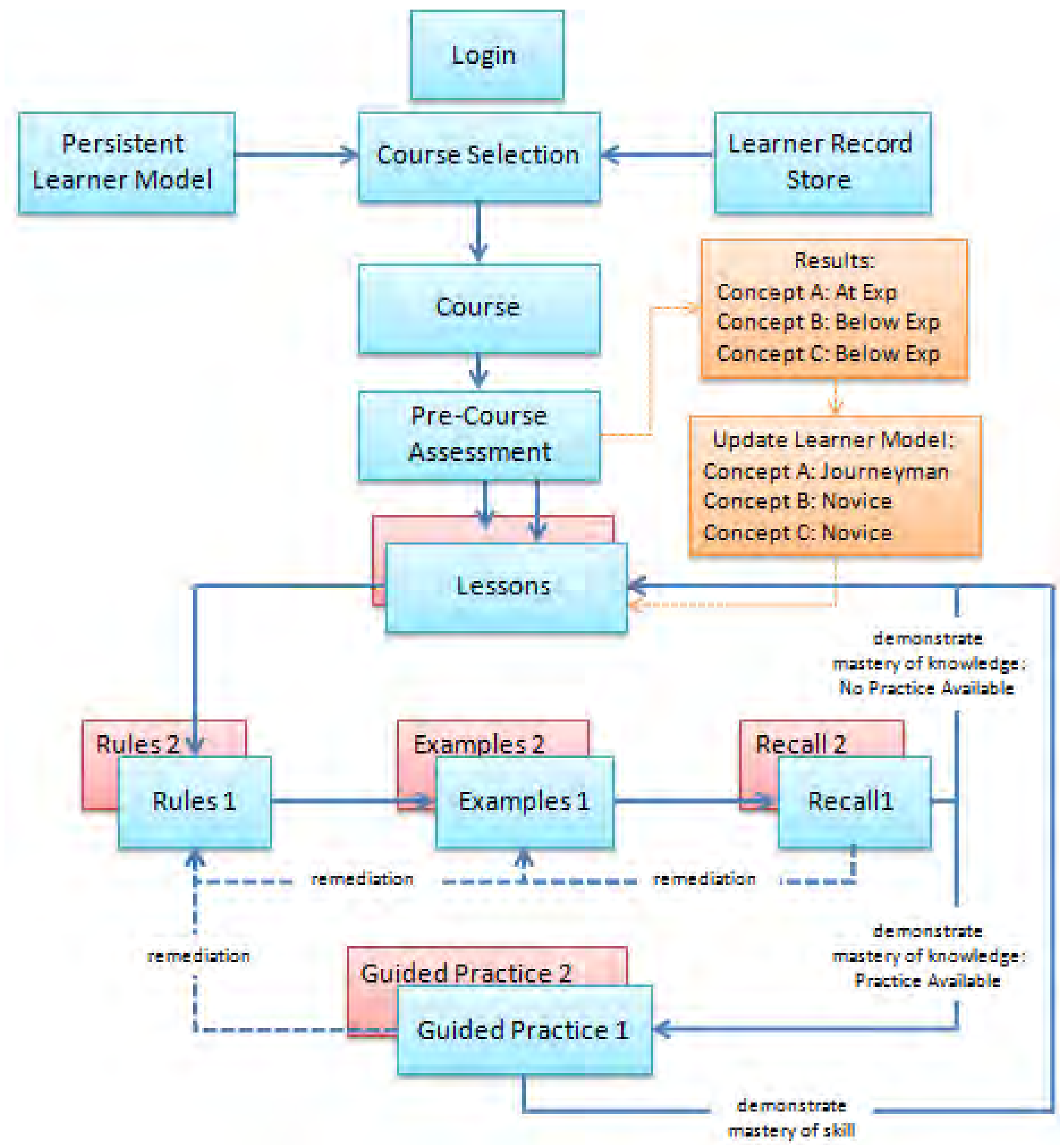

Fig. 3 GIFT's EMAP (Goldberg and Hoffman 2015)

With a current layout of the functions GIFT supports from an instructional management perspective, the remainder of the research outline will target specific utilities of interest that a domain-independent architecture needs for wide use across military, academic, and industry settings. Specific goals of desired functions will be presented, followed by recognized subvectors of interest that require substantial research to determine their optimal conditions for use in a learning event. As GIFT is intended to be a unified standard for building ITSs of all kinds, it is important to recognize the varying instructional management practices that can be implemented and what conditions are best for their use.

6. Instructional Management Research Goals and Challenges

The foundational goal of adaptive training research at the ARL is to model the perception, judgment, and behaviors of expert human tutors to support practical, effective, and affordable learning experiences guided by computer-based agents. To this end, 5 primary challenges in instructional management for adaptive training systems have been identified and are discussed in this section.

In the following subsections, we review the specific overarching themes associated with instructional management research in GIFT. Each theme is represented as a subvector in this research outline. While reading through these research thrusts, make sure to conceptualize their application across various training environments and use cases. While the subvectors can be somewhat confined in terms of instructional management intent, options for how they can be applied across all types of training environments are vast. This includes considering individualized versus team-based training events and the technologies being applied to facilitate the training itself.

6.1 Guidance and Scaffolding

Scaffolding is a term used to describe the application of instructional supports to assist a learner in developing knowledge and skills that the learner would not achieve when left to their own devices. Holden and Sinatra (2014) define scaffolds as a temporary application of strategy that is gradually removed ("faded") once a learner demonstrates an increase in proficiency or skill. The word 'strategy' is used loosely here, as it can be a number of interventions that range from guidance, feedback, scenario/problem manipulation, and remediation. Prior to the advent of computer-based training environments and ITSs, an expert adult or peer (parent, teacher, classmate, teammate, etc.) provided scaffolding practices. This individual acted as an expert facilitator of KSAs required for learning, motivator, model, and means for the learner to reflect (Puntambekar and Hübscher 2005). As such, much of the applied guidance and scaffolding practices in adaptive training environments are based on what effective instructors and tutors do in real life. In examining models of expert human tutors, the following themes have been identified for effective interaction:

- Demonstrate credible knowledge of the domain under training (e.g., tactical combat casualty care).
- Read cues from the learner and adapt instruction in real time to meet their changing needs.

- Encourage question asking.
- Provide indirect feedback.
- Assess learning often.

When designing scaffolds and the logic associated with their execution, 3 dimensions require consideration: what to scaffold, when to scaffold, and how to scaffold (Azevedo and Jacobson 2008). With respect to GIFT, each of these dimensions must be conceptualized in a domain-agnostic fashion. The first consideration that will dictate how to proceed is based on available tools and methods for scaffolding. In this vein, the mode of interaction and the specific training application itself will determine what approaches can be implemented (Goldberg and Cannon-Bowers 2015). For instance, interacting in VBS3 affords different scaffolding strategies when compared with interacting with a negotiation trainer on a tablet. The type of state (e.g., performance, affective) information being monitored in the learner model (Shute et al. 2013), the type of communication interfaces available for presenting information (e.g., GIFT's Tutor User Interface, smartphone, smart glasses, haptic device), and the type of adaptations supported by the training application (e.g., changing the weather in VBS3 to increase the complexity of scenario) all impact the types of scaffolds that can be built to support a specific course or lesson.

Once one recognizes the available tools to trigger and support scaffolding practices, determining what to scaffold must be addressed next. What to scaffold can be represented in a generalized fashion and is based on defined learning objectives and barriers to a learner performing successfully. This could include scaffolding specifically on the cognitive level that accounts for the domain or the task procedures themselves. Or scaffolds can account for different constructs associated with the learning process, such as metacognition (i.e., to regulate goal planning, performance monitoring, and help-seeking) and affect (i.e., to regulate motivation, boredom, frustration, and confusion) (van de Pol et al. 2010). Recognizing what one wants to scaffold along with what tools and methods one has to support those types of interventions will lend itself into building the specific scaffolds for implementation.

With scaffolds conceptually established, the next step is building logic for determining when to apply a scaffold and how to appropriately fade/adapt its use to promote efficient transfer of execution. A common perspective to account for this challenge is based on Vygotsky's (1978) ZPD. ZPD is an optimal and efficient zone of learning that elevates the student from his/her current and actual developmental level to one of more potential through balancing challenge with ability and through formative guidance to enhance skill (Vygotsky 1978). In its

simplest form, the ZPD creates a formalized state space representation that enables a system to contextualize what a learner is experiencing for a given training domain. For example, if a training system launches a scenario with a preconfigured difficulty setting of expert and a trainee's skill state is defined as journeyman, the system may trigger specific scaffolds that are intended to support the maturation of skill levels to meet the challenge level of a selected scenario. In this instance, if performance assessments associate execution with increased skill levels, the system must be able to recognize this shift and fade scaffolds. From the opposite end, if a learner demonstrates skills that fall below his or her predicted ability levels, the system must be able to appropriately trigger scaffolds to compensate for that inaccurate upfront classification. This must be possible for both dynamic scenario-driven tasks as well as for training applications that use discrete problem sets that allow adaptation between each problem.

Much of the described scaffolding- and guidance-focused end-state objectives are composed of a mix of inner-loop and outer-loop pedagogical practices. In short, the training application being used will dictate the type of scaffolding that can be executed. While GIFT is domain-agnostic, once a training application is applied, the next step is conceptualizing what adaptive functions are supported and what authoring processes are required. In an ideal end-state, a constraint-based, intelligent pedagogical agent can be applied to guide the authoring processes and to manage run-time decisions. These decisions center on selecting appropriate domain independent strategies, translating strategies into optimal tactics (actions) based on situational context, and then presenting the tactic (take action) through the delivery of feedback, providing direction, or changing the training environment.

When considering scaffolding for adaptive training environments, several needed areas of research emerge. These areas are relevant due to the advancing popularity in ITSs and the relative infancy of these environments applied in military contexts. Holden and Sinatra (2014) identify several necessary future research areas involving scaffolding and GIFT. One involves defining the different focuses to scaffolding and distinguishing the conditions under which its implementation is best. Several specific types of scaffolding exist on a theoretical level, including conceptual, metacognitive, procedural, and strategic (Hannafin et al. 1999). As such, the word 'scaffold' applied in this context is as a very broad term that associates with multiple forms of transitions, interventions, and adaptations performed by a system. In terms of pedagogical intent, a range of scaffolds can be applied to associate with the following:

- **Error-Sensitive Feedback:** An intervention triggered when the learner commits errors that are either individually or cumulatively significantly divergent from the ideal as defined in the expert model of the ITS.

- **Mastery Learning:** A strategy where the ITS ensures that the learner masters (can recall and apply) prerequisite lessons or concepts before allowing the learner to move on to the next lesson/concept.
- **Adaptive Spacing and Repetition:** A strategy where the learner more easily recalls knowledge items/objects when the knowledge is exposed to the learner repeatedly over a long time-span rather than repeatedly studied during a short span of time (Benjamin and Tullis 2010; Dempster 1989).
- **Metacognitive Prompting:** A strategy where the ITS encourages the learner to self-reflect and evaluate, self-explain, and self-correct rather than provide the answer directly.
- **Fading Worked Examples:** "[A] step-by-step demonstration of how to perform a task or how to solve a problem" from which parts have been deliberately removed or faded (Clark et al. 2006, p. 190).

While scaffolds are very domain-relevant and application-dependent, tools and methods must be established in GIFT to support building and implementing optimal scaffolds across all types of supporting training environments. This also extends into investigating scaffolds for team-based training events. From this association, the following potential research questions arise:

- What is the best approach to the authoring run-time instructional management logic in GIFT?
- Are there pedagogical best-practice heuristics that generalize across training environments with varying levels of interactivity and user control?
- How do scaffolding best practices translate to collaborative and team-based training exercises?
- What are the variations in feedback considerations when comparing individualized instruction with team-based training?
- What role do worked examples play in military relevant training environments, and how can SMEs use this pedagogical function to create better training?
- What probabilistic modeling techniques account for system uncertainties and optimize instructional management practices and tutorial planning logic over time to avoid solely deterministic execution?
- What architectural modifications are required to support contextualized feedback prompts that adhere to a domain-agnostic pedagogical structure

(i.e., communicating scenario relevant feedback by including interaction data available in log files)?

- How much control should the learner have on guidance and scaffolding support (i.e., help seeking)?
- When should guidance and scaffolding be on demand (e.g., learner requests hint), triggered by a student/system event or state, or blended?
- What performance factors and individual differences tracked in the learner model should moderate scaffold selection and fading logic?
- How do generalized scaffolding techniques vary across training delivery modalities (e.g., laptop, smartphone/tablet, simulators, and smart glasses/head-mounted displays)?
- How can SMEs embed scaffold supports in virtual world game environments commonly used for training purposes (e.g., VBS3)?
- Under what conditions does an adaptive training environment provide guidance versus adapting the scenario or problem selection?
- What assessment types trigger variations in scaffolding techniques (e.g., conceptual versus affective versus procedural versus metacognitive)?

6.2 Social Dynamics and Virtual Humans

In this research subvector, we review end-state goals associated with the role of social dynamics and virtual humans in managing instruction within adaptive training environments. This line of research associates with tenets of Social Cognitive Theory in that learning is theorized to be an inherently social process (Bandura 1986; Vygotsky 1978). As such, techniques should be applied to account for high-valued social elements that can potentially improve a piece of educational technology. In addition, Army task domains can involve highly socialized interactions. To support these task characteristics, adaptive training systems should account for the types of interactions a Soldier might face (e.g., negotiating with a village elder) and the variables that may influence their course of action (e.g., cultural norms for greetings and negotiations). From an adaptive training perspective, social dynamics and virtual human research is focused on the following:

- Using technology and AI to replicate interactive discourse common in educational and operational settings.

- Using technology to embed social elements in the environment, such as virtual humans, to create a social grounding function for delivering information/guidance.
- Using technology and AI to create realistic and reactive virtual humans as training elements in a simulation or scenario (e.g., role player and teammate).
- Using technology to create a social forum for the purpose of supporting peer-to-peer and collaborative learning, both from a real-time perspective and a time-agnostic approach allowing interaction at convenience.

Each referenced focus area is based on a specific social element of interest to the GIFT community. Of importance is the application of these elements within the standardized architecture inherent to GIFT. Specifically, how can the tools and methods built to afford these capabilities be translated to support ease of application within any type of training event and within any type of training environment supported by GIFT? Each identified element associates distinctly different research questions and associates distinctly different scientific disciplines. It is a very broad subvector of instructional management with many dependencies to other elements of the GIFT research program.

In the case of using ITS technologies to replicate interactive discourse, an end-state goal is to establish state-of-the-art natural language processes to create a robust tool capable of dynamic question and answer (QandA) exchanges. In this instance, we want a training environment to be able to push a question to a learner and a trainee to be able to ask questions of the ITS, ideally through natural language and open response input methods. As highlighted previously, a characteristic of an effective tutor is one who encourages a learner to ask questions. This process in itself promotes learning through abstraction and reflection. As such, we need a discourse capability that can accurately interpret user responses and intent as they relate to the semantic space of instruction, and we want this capability to associate with pre-existing training applications (i.e., natural discourse QandA in parallel with executing a VBS3 scenario). This capability can be applied in multiple training instances and under many conditions, including 1) discourse to support reflective QandA sessions to promote higher order cognitive thinking, 2) discourse to support training events that involve social exchanges to meet certain negotiation objectives, and 3) discourse to support realistic communication with virtual entities in an environment that associate with both friendly and opposing forces. Much like scaffolding capabilities, the application of natural language discourse in an adaptive training event associates many dependencies across the various research vectors. Specifically, domain modeling, authoring processes, and architecture requirements

are the greatest considerations when it comes to implementing this approach to instructional management.

Next, virtual humans are identified as key technology pieces in extending adaptive training experiences to account for varying roles in the learning process. From an ITS support perspective, virtual human research is focused on the application of technology to provide an interactive communication layer that grounds all system-generated prompts with a social element. An overarching intent is to facilitate interaction and communication with a computer in a way that is natural and realistic. The goal is to support highly engaging and interactive experiences through socialized sequencing of interaction and enhancing system communication by interfacing with a learner through comfortable modalities. Much of the prior research in this area focuses on the trust and perception of technology in facilitating a role traditionally managed by a person and the impact on motivation and effort (Holden and Goldberg 2011; Kim and Baylor 2006; Veletsianos 2010; Veletsianos et al. 2009).

Virtual humans can also facilitate critical role players in training events. In these instances, AI methods allow virtual entities to realistically react to environmental stimuli and user inputs in a nonscripted fashion, making the experience more natural and engaging. Social media technologies are believed to offer innovative tools for instructional management practices that have yet to be fully taken advantage of. As a result, research is required to better understand how best those tools and methods can be applied. This involves the use of social media as a means to collect valuable user input on training materials to determine objects that need modifications, as well as investigating how social media can be used to promote collaborative learning, competition, and distributed guidance.

6.3 Metacognition and Self-Regulated Learning

SRL theory describes the process of taking control of and evaluating one's own learning and behavior (Butler et al. 2011). As a higher-order cognitive function, SRL is guided by metacognitive processes (i.e., the knowledge and regulation of one's own cognition), strategic actions and behaviors (i.e., planning, monitoring, and assessing one's own performance), and motivational components (i.e., goal setting and self-efficacy) (Flavell et al. 1985; Schraw et al. 2006). These functions allow self-regulated learners to set goals, monitor their progress toward defined goals, and adapt and regulate their cognition, motivation, and behavior to reach the specified goals (Anderman and Corno 2013; Bransford et al. 2000). These characteristics also associate with desired competencies within the ALM that adaptive training solutions are intended to instill. As such, research in the

instructional management vector is focused on the application of models and strategies for enhancing metacognitive awareness and regulation.

This approach to instructional management varies from traditional guidance and scaffolding techniques, as it focuses on behavior and application of strategy, rather than on task-dependent performance. One such question is based on GIFT supporting SRL and the efficacy of defining persistent metacognitive strategies that can be applied across domain applications. Currently, GIFT pedagogy is heavily focused on error-sensitive feedback. It works with system authors by translating instructional strategy recommendations communicated by GIFT's pedagogical module into tactics as they relate to the specific training context. These tactics are used during ITS runtime and selected based on a learner's individual differences. Currently, feedback in GIFT is domain-dependent and requires explicit content linked to each concept modeled. When it comes to metacognitive feedback, what are the implications to a domain-independent approach? First, modeling techniques need to be developed to monitor an individual's practice of metacognitive strategies that can be expressed in a generalized format. An example would be incorporating a combined modeling approach, as described in Biswas et al. (2014), or by adapting a help-seeking model, as highlighted in Koedinger et al. (2009).

One such approach is researching and establishing models based around commonly available GIFT interactions (e.g., request hint button). How can we use these available data inputs to build a representation of how effective students use the interface to solve problems and troubleshoot errors? This approach can aid in detecting learners not practicing good metacognitive behaviors through machine learning and data mining practices and can be used to trigger feedback interventions to improve their understanding of available strategies. With modeling techniques in place, generic strategies and tactics can be identified that are based on effective metacognitive behavior. In this instance, the generic strategy of "provide guidance" can be linked with a generic tactic of "you are ignoring available resources", thus preventing any explicit authoring from a system developer. While tactics can be represented in a domain-independent format, their effect is relatively unknown.

Regardless of the instructional management intent, just like all other facets of instruction, metacognitive tutoring depends on sound assessment practices that ultimately inform the type of intervention to execute. Due to difficulties in inferring upon interaction data alone, another area of interest is the application of alternative assessment techniques to better gauge an individual's understanding of the task and the resources available to meet objectives. This involves inference procedures on interaction patterns and existing performance outcomes, as well as devising approaches to collect new information that is not implicitly available in the training environment.

Beyond all of the associated types of scaffolds that can serve metacognitive development, how does one implement such practices? A challenge that must be addressed is establishing an authoring environment and workflow for supporting SRL-derived modeling techniques and linking outputs to prescribed strategies that influence the regulation of metacognitive behaviors. The ultimate goal is to support and influence a learner's approach to problem solving and learning in general. While the research identifies multiple examples of successful strategy implementation, what the literature lacks are guidelines for when best to instantiate them based on the domain being trained and the environment the interaction is taking place within. To enhance GIFT's authoring functionalities, a generalized ontology is required that links specific instructional strategies and techniques with high-level domain-relevant content along with the types of tutoring environments and the services they can afford. By defining these relative dependencies, an ITS developer can embed empirically recommended metacognitive tutoring functions based on characteristics associated with the content being produced.

In the context of tutor development within the GIFT architecture, the goal is to establish a set of strategies the framework can support and conceptualize their application for determining future authoring requirements to support their implementation, both from a modeling and pedagogical delivery standpoint. In accordance with this subvector of instructional management research in adaptive training environments, research questions of interest include the following:

- What modeling implications are associated with supporting instructional management to develop metacognitive skills?
- What architectural modifications are required to infer metacognitive relevant states from raw interaction data outputs?
- What combination of assessment techniques provides the most accurate prediction of metacognitive strategy application?
- What metacognitive strategies can be inherently assessed across all domains regardless of the training application?
- How do metacognitive strategies translate across domains and training environments?
- What educational data mining techniques can be applied to infer self-regulated learning abilities from common GIFT produced log files?
- How do scaffolding practices of delivery and fading for domain-specific guidance functions translate to metacognitive tutoring?

- Can metacognitive tutoring models and strategy implementations be developed by nontechnical SMEs?

6.4 Optimizing the Selection of Tactics

Our fourth goal is to optimize the selection of tactics—domain-specific actions by the tutor—to provide the greatest opportunity for performance, learning, retention, and transfer. In GIFT, tactics are the actions taken by the tutor in response to learner states and instructional context (e.g., conditions of the scenario or problem presented), as shown in Fig. 2, and are constrained by available options provided during the authoring process. Improving the usability and efficiency of authoring tools will likely result in a greater number of available options for adaptive training domains.

Unlike instructional strategies, which are derived from good pedagogical practices–based learning theory and influenced by the learner's states, tactics are domain-specific actions by the tutor and may not be generalized across all task domains. Research is needed to determine methods to select the best possible tactic given the selected instructional strategy, the training domain, and the availability of tactics.

Modeling the expert behaviors of human tutors may be a starting point but accurate assessment methods are needed for both individual and team level states. These states are critical in selecting appropriate strategies (plans for action) and tactics (actions; e.g., assessments, feedback, questions, and changes to the training environment) per the Learning Effect Model (Sottilare et al. 2013b) as shown for both individuals (Fig. 2) and teams (Fig. 4). Assessment of team states may also be useful in determining constraints to be monitored by tutoring agents and interactions with the learner and the training environment as shown in Fig. 2.

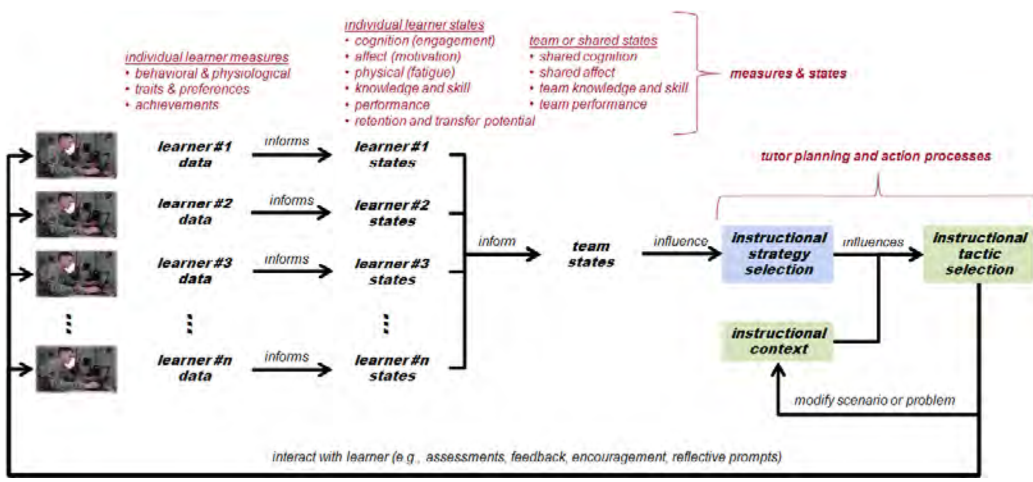

Fig. 4 Team learning effect model (Sottilare in press)

6.5 Personalization (Occupational and Noncognitive Factors)

Personalization of content to an individual student's interests has been shown to have a positive impact on learning, retention of information, and motivation (Cordova and Lepper 1996). Further, using this strategy has also demonstrated positive effects in transfer performance, which is the ability to extend what was learned to related tasks (Walkington 2013). This instructional strategy is generally referred to as context personalization, and has been shown to be effective in adaptive computer environments (Anand and Ross 1987; Cordova and Lepper 1996; Walkington 2013).

The majority of the context personalization research has been in the area of mathematics, with learning and transfer gains being found in areas such as algebra, fractions, and word problems (Anand and Ross 1987; Cordova and Lepper 1996; Ross et al. 1986; Walkington 2013). The self-reference effect, or the ability for reference to the self to improve memory (Symons and Johnson 1997), is often studied along with context personalization by including the student's name or personal information in the materials (Anand and Ross 1987; Cordova and Lepper 1996; Sinatra et al. 2014). In addition to mathematics, the self-reference effect has been examined in domain areas such as science and deductive reasoning (Moreno and Mayer 2000; Sinatra et al. 2014).

By personalizing the context of the material that is learned, it could have both affective and cognitive impacts on the individual. Motivation and positive attitudes toward the material has been shown to increase in personalized contexts (Anand and Ross 1987; Cordova and Lepper 1996). In an adaptive system with self-entered preferences, the student may feel that the system is taking his or her preferences into account if interest personalized questions are given, which may result in more positive feelings toward the system (Ritter et al. 2007). Additionally, by aligning examples and information in the content to be learned with the previous knowledge base of the individual, it may both increase interest in the training and lessen the mental workload required to learn the material (Anand and Ross 1987; Ku and Sullivan 2002; Ross 1983; Sinatra et al. 2014).

Research has suggested that by using examples that are consistent with one's college major and area of expertise it can improve learning outcomes. Specifically, it was found that nursing students who received medical examples had more positive outcomes than those who were given teaching examples. Conversely, education students who were given teaching examples on the same task performed better than when they were given medical examples (Ross 1983). Follow-up work found that both individually selected interest preferences and general adaptation to interests (based on major) showed positive learning outcomes (Ross et al. 1986).

The reason behind these effects may be 2-fold: By using examples that are consistent with one's knowledge base, it may be inherently more interesting to the individual; further, it may reduce the amount of cognitive effort that is necessary to engage with the material since the student already has a good understanding of the context.

It would be advantageous to continue to research into the impact of context personalization in adaptive training programs. Current ITS systems, such as GIFT, offer more flexibility and features than systems and computer programs that were developed in the original context-personalization research conducted in the 1980s and 1990s. Additionally, as a domain-independent framework, GIFT can be used to examine the impact of context personalization in a variety of other domains, whereas in the past the research has primarily focused on math instruction. One approach to context-personalization research that can be taken with GIFT is to do work similar to Ross (1983), in which the context of the problems and materials are specifically matched or mismatched with the individual learner's specialty area. In the context of military training, a Soldier's MOS and near-term assignments can be used to personalize a training experience to better prepare that individual for the environment they will be operating within.

Rather than using mathematics as the domain of interest, a military-relevant domain can be chosen. Providing materials that are matched to the individual learner's specialty area is expected to have a positive impact on learning and attitudes toward the experience. Learning outcomes are expected to be improved, as the individual will not already have an understanding of the context of the provided examples but also will be able to easily see why it is relevant to their own job.

To support personalization, additional studies could examine the impact of allowing learners to select the context of the questions they will receive based on their own preferences or the task that they will be engaging in. In many military-related tasks there are subtle differences in the task that will be performed based on the geographic location of their assignment. For instance, if an individual is tasked with interacting and negotiating with individuals from a culture other than their own, they may engage with a negotiation tutor. However, depending on the culture that they are to engage, there may be different phrases or customs that should or should not be used. The basic elements of negotiation will be similar but the questions and materials can be edited to have geographic and culturally specific examples that will be more consistent with the actual experience the individual will have. Research can be conducted on the level and types of material and assessment personalization that results in positive outcomes and performance.

To support this type of research and personalization, ideally in an ITS, general questions can be created, and based on learner entered or selected information they can be personalized for the individual student. The following is a math example to demonstrate simple question context personalization:

- General question: "You have 4 _____. You are offered 5 _____ in exchange for half of your _____. How many ______ do you have after the trade?"
- If you were using the context of fruit, the problem could read "You have 4 apples. You are offered 5 oranges in exchange for half of your apples. How many pieces of fruit do you have after the trade?"
- Additionally, if you were using the context of books, the question could read "You have 4 science fiction novels. You are offered 5 mystery novels in exchange for half of your science fiction novels. How many novels do you have after the trade?"

In this example, a general question is authored and then specific items are added in to change the context or topic of the question. Research can examine the impact of providing questions and examples that are consistent (and inconsistent) with the learner's job or interest areas. To do so in GIFT, edits may be needed to be made such that GIFT could store a bank of questions that are similar to each other but differ in context. The version of the questions that are consistent with the learner-selected context can then be selected by the system and used during training. Additional techniques for personalization of questions and materials may include allowing for user-entered information (such as the individual's name) to be integrated into the questions.

If these or similar studies are shown to be successful, multiple versions of training question domains can be generated in ITSs, resulting in the learner engaging with the one that is most relevant to themselves based on previous experience and self-entered preferences. As functionality is being developed in ITSs to track student learning history and characteristics, it may also be advantageous to store student preferences, interests, and the expertise area of the individual. This stored information can then be used for context personalization to ultimately increase learner performance and retention in ITSs such as GIFT.

While personalization is an instructional strategy, research based on it will ultimately impact both the areas of authoring and learner modeling in GIFT. Authoring tools and/or support will need to be added into GIFT to allow for personalized questions and storing personalized question banks. Storage of learner preferences and information will need to be stored by GIFT's learner module such that they can be used in future trainings and engagements with the system.

The following are personalization-related research questions:

- Will matching the context of materials to be consistent with a learner's job or interest area lead to increased learning and performance?
- Will individuals who receive context personalized materials have more-positive attitudes toward the tutoring system?
- What types of personalization (e.g., based on self-selected interest, based on job, and based on task) will have the best outcomes?
- Are their individual differences that will moderate the benefits of personalization? If so, what types of learner characteristics should result in the use of personalized materials?

7. Interdependencies with Other Adaptive Training Research Vectors

This section examines interdependencies between instructional management and the other 5 adaptive training research vectors (Fig. 5). This discussion forms the basis for the sequencing of research and ultimately bringing adaptive training capabilities into a state of practice.

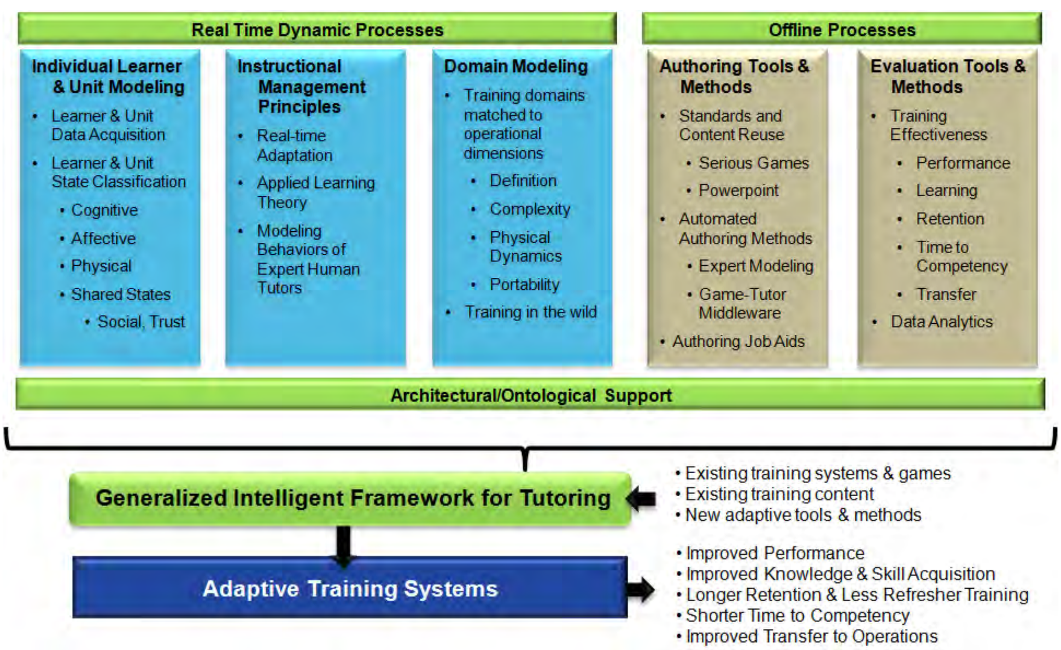

Fig. 5 Adaptive training research vectors

Accurate methods to classify individual and team learner states are a necessary precursor to selecting optimal instructional strategies, as noted in the learning effect models for individual learners (Fig. 2) and teams of learners (Fig. 4). In turn, instructional strategies along with instructional context are necessary precursors to selecting optimal instructional tactics and ultimately significant effect on desired outcomes: learning, performance, retention, and transfer.

As such, it is difficult to conceptualize the application of instructional management focused research without involving other vector components of the GIFT program. Therefore, the dependency of instructional management research on other functional areas of the architecture is significant.

7.1 Learner Modeling and Instructional Management

Adaptive training systems are learner-centric systems. Independent of the domain under training, accurate modeling of the learner is critical to driving instructional decisions in adaptive training systems. However, collection and maintenance of this data may be costly, so it is necessary to select measures and states that significantly impact our desired outcomes: learning, performance, retention, and transfer. Research is needed to determine what this dataset will look like. Candidates abound in the literature but in general these include transient data/states, cumulative states (building over time), and enduring data/states (Paneva 2006). Learning falls into both transient and cumulative states. It is necessary to understand progress toward domain competency in addition to measures of near-term performance, and it is important to understand how domain-specific learning (skills) decay over time.

Transient measures of importance include individual behavioral and physiological data, and cognitive, affective, physical, and social states to represent learning. Cumulative measures include achievements (e.g., certifications, training, education, and experiences), affiliations, work history, and domain competency. More-enduring information about the learner might include gender, culture, first language, physical constraints (e.g., colorblind/deaf), values, personality attributes, or other trait-based information (Sottilare and Brawner 2014). All of these measures/states are potential drivers for adaptive training decisions.

In terms of instructional management, sound pedagogy is reliant on accurate representation in the learner model. It is important to identify variables in a learner model that moderate learning, account for variance in performance, and can be accurately assessed in real time for informing strategy selections. Selecting an inappropriate strategy and tactic combination can result in negative learning outcomes and can ultimately impact the perceived value of the system.

7.2 Domain Modeling and Instructional Management

In GIFT, instructional management takes place in 2 modules/processes within the learning effect model. One process is instructional strategy selection within the pedagogical module. The second is within the domain module where specific tactics or actions are selected based on the strategy selection and instructional context. An important component of instructional management is translating a generalized strategy into a tactic that can be executed within a specific training environment. This requires understanding what knowledge components make up a domain and what tools are available to guide a learner and adapt the training event.

In addition, domain modeling plays a critical role in enabling the use of reusable learning objects. When applying instructional management practices in an outer-loop capacity through GIFT's EMAP (Fig. 3), a well-designed domain model can be used to identify content that can be presented to a learner along with data that supports its application. This supports ease of authoring as well, as a developer can leverage existing content if the domain model has overlap with existing course representations.

7.3 Authoring Tools and Instructional Management

Authoring tools and methods are needed to configure instructional management practices across all adaptive training systems and domains of instruction. There are 2 types of authors that must be considered. First, training developers and SMEs are targeted as end-users. These individuals will use GIFT services to create highly personalized adaptive training events by leveraging the pedagogical models established within available baseline versions. While a training developer and SME are well versed in the knowledge components of a domain, they will lack many of the skills required to build adaptive training solutions. The authoring tools must be designed to compensate for a developer's lack of understanding across the various disciplines involved in creating such systems. Building tools that guide the various authoring processes is critical to the success of GIFT outside of the laboratory setting. It will also be important that these tools help individuals maintain a contextualized awareness of what they authoring and how that will be translated into a run-time instantiation.

The second author to consider is a research scientist interested in instructional management research within adaptive training systems. These individuals will require the ability to manipulate various components of the GIFT modules to support their research. Using the ATLEC as a guiding function to highlight instructional management research in ITSs, authoring processes must be

established to configure the inputs, processes, and outputs of the pedagogical module. This includes defining the variables from the learner model that moderate strategy selection (with a large assumption that the modeling techniques applied for that variable are accurate), defining the logic and policies that dictate what strategy to select based on learner data, and defining how that strategy is translated into a specific tactic to be executed in the environment. This is greatly different from the training developer/SME example, as the only intended authoring function of this group is defining the tactic that would be executed.

Another avenue of authoring that must also be addressed is metadata, which plays a large role in instructional management within a domain-independent framework, as it provides a way to describe your content and guidance functions in a relatively generic fashion. In terms of authoring, tools must be developed to facilitate easy application of metadata to learning objects. Research is required to determine how best to support this function.

7.4 Evaluation and Instructional Management

Training effectiveness research is focused primarily on the impact of instructional management practices on learning outcomes of interest: performance, retention, and transfer. To optimize the application of adaptive training in the Army, automated training effectiveness tools are required to run analyses as data become available. Much of these capabilities are researched within communities dedicated to educational data mining. The goal is to test pre-established configurations to determine their impact on learning and adapt instructional management policies to better optimize learning experiences.

A goal of instructional management in GIFT is to optimize performance and competency outcomes through personalized training experiences that adapt to an individual's KSAs. A connection between big data and instructional management is applying large datasets from prior course interactions to update and improve technique and strategy implementations across all available courses. A challenge with defining instructional management logic in a domain-independent context is that it requires generalizability across applications. An issue with instructional strategy-based research is that an approach taken in one domain is hard to translate to a different one without performing extensive research to validate its application. In addition, it is difficult to define definitive instructional management logic based on these uncertainties. As such, big data can be used to account for this uncertainty by applying machine learning and data mining techniques to assess specific causal relationships between instructional practices and outcomes on performance,

retention, and transfer. This application of big data is used to reinforce instructional management models by optimizing itself over time as more and more data are made available.

7.5 Architecture and Instructional Management

Managing instructional strategy selection and tactic delivery depends upon multiple components of GIFT. This associates domain modeling to apply context to a pedagogical decision, learner modeling to provide trainee relevant information that triggers a pedagogical intervention, authoring to provide a means for building these linkages and representations, and training effectiveness to determine if a strategy or set of strategies had an effect on performance-related outcomes. This highlights an important point; while each of the aforementioned components of instructional management has separate processes, the architecture is the component that dictates implementation design and development.

In terms of architecture, GIFT end-state goals require potential integration with a number of technologies that facilitate varying roles of instructional management practices. These technologies include tools and methods to support content management, natural language processing, text-to-speech processing, virtual human authoring and configuration, social media framework connections, and training application manipulations (e.g., manipulating the weather in a virtual world). In addition, specific architectural modifications will be required to perform tasks inherent to the current standards of GIFT, including methods to create messaging templates used to auto-populate feedback scripts with context relevant information established in log files, the ability to personalize strategy selections on an outer- and inner-loop capacity across learners and teams of learners, and the application of actionable metadata and API statements to appropriately link learner information and prior experience with appropriate training and optimized configurations. In dealing with a domain-agnostic intelligent framework such as GIFT, the use of machine learning and data mining techniques is required to reinforce and optimize pedagogical logic over time.

8. Conclusions

This report outlines the ARL’s plans for conducting research in adaptive training and education to support the ALM. Specifically, this report relates to instructional management and the answer to the following question: What adaptive instructional methods (strategies, tactics, and techniques) are most effective for individual and team-based military training and educational domains?

This report outlined the following goals:

- Model the perception, judgment, and behaviors of expert human tutors to support practical, effective, and affordable learning experiences guided by computer-based agents.
- Leverage prior research in the learning sciences and AI communities (both theoretical and empirical) to establish a set of best practices on how to author and execute techniques, strategies, and tactics across any domain of instruction.
- Discover and develop modeling functions that account for uncertainty across policies informing pedagogical decisions (e.g., content delivery, course navigation, and guidance).
- Personalize instructional technique and strategy selections based on individual differences informed through empirical evaluations and reinforcement machine learning methods.
- Develop authoring tools grounded in cognitive and instructional theory and informed by empirical research to assist training managers, developers, and SMEs in building pedagogically sound training experiences without the requirement of programming.
- Support individual and team training (e.g., small unit and collective training) and education (e.g., collaborative learning and problem-solving) experiences.

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List of Symbols, Abbreviations, and Acronyms

σ	sigma
AAR	after-action review
AI	artificial intelligence
ALM	US Army Learning Model
ARL	US Army Research Laboratory
ATLEC	Assistive Technology Learning through a Unified Curriculum
DIS	distributed interactive simulation
EMAP	Engine for Management of Adaptive Pedagogy
GIFT	Generalized Intelligent Framework for Tutoring
ITS	intelligent tutoring system
KSA	knowledge, skill, and ability
LEM	Learning Effect Model
MOS	military occupational specialty
QandA	question and answer
SME	subject matter expert
SRL	self-regulated learning
TandE	training and education
BVS3	Virtual Battlespace 3
WFO	Warfighter outcome
ZPD	zone of proximal development

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8 (PDF) ARMY RSCH LAB – HRED
SIMULATION & TRAINING
TECHNOLOGY CENTER
RDRL HRT COL G LAASE
RDRL HRT I MARTINEZ
RDRL HRT T R SOTTILARE
RDRL HRT B N FINKELSTEIN
RDRL HRT G A RODRIGUEZ
RDRL HRT I J HART
RDRL HRT M C METEVIER
RDRL HRT S B PETTIT
12423 RESEARCH PARKWAY
ORLANDO FL 32826

1 (PDF) ARMY RSCH LAB – HRED
HQ USASOC
RDRL HRM CN R SPENCER
BLDG E2929 DESERT STORM DR
FORT BRAGG NC 28310

1 (PDF) ARMY G1
DAPE MR B KNAPP
300 ARMY PENTAGON
RM 2C489
WASHINGTON DC 20310-0300

ABERDEEN PROVING GROUND

12 (PDF) DIR USARL
RDRL HR
L ALLENDER
P FRANASZCZUK
R SOTTILARE
RDRL HRM
K MCDOWELL
D HEADLEY
RDRL HRM AL
P SAVAGE-KNEPSHIELD
C PAULILLO
RDRL HRM B
J GRYNOVICKI
RDRL HRM C
L GARRETT
RDRL HRS
J LOCKETT
RDRL HRS B
M LAFIANDRA
RDRL HRS D
A SCHARINE

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